RAPID ASSESSMENT OF REDEVELOPMENT POTENTIAL IN MARGINAL OIL FIELDS, APPLICATION TO THE CUT BANK FIELD

A Thesis

by

LUIS ELADIO CHAVEZ BALLESTEROS

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

December 2004

Major Subject: Petroleum Engineering

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Approved as to style and content by:

Duane McVay (Chair of Committee)	Walter Ayers (Member)
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ABSTRACT

Rapid Assessment of Redevelopment Potential in Marginal Oil Fields, Application to the Cut Bank Field. (December 2004)

Luis Eladio Chavez Ballesteros, B.S., Universidad Industrial de Santander

Chair of Advisory Committee: Dr. Duane McVay

Quantifying infill potential in marginal oil fields often involves several challenges. These include highly heterogeneous reservoir quality both horizontally and vertically, incomplete reservoir databases, considerably large amounts of data involving numerous wells, and different production and completion practices. The most accurate way to estimate infill potential is to conduct a detailed integrated reservoir study, which is often time-consuming and expensive for operators of marginal oil fields. Hence, there is a need for less-demanding methods that characterize and predict heterogeneity and production variability. As an alternative approach, various authors have used empirical or statistical analyses to model variable well performance. Many of the methods are based solely on the analysis of well location, production and time data.

My objective is to develop an enhanced method for rapid assessment of infill-drilling potential that would combine increased accuracy of simulation-based methods with times and costs associated with statistical methods. My proposed solution is to use reservoir simulation combined with automatic history matching to regress production data to determine the permeability distribution. Instead of matching on individual cell values of reservoir properties, I match on constant values of permeability within regions around each well. I then use the permeability distribution and an array of automated simulation predictions to determine infill drilling potential throughout the reservoir.

Infill predictions on a single-phase synthetic case showed greater accuracy than results from statistical techniques. The methodology successfully identified infill well locations

on a synthetic case derived from Cut Bank field, a water-flooded oil reservoir. Analysis of the actual production and injection data from Cut Bank field was unsuccessful, mainly because of an incomplete production database and limitations in the commercial regression software I used.

In addition to providing more accurate results than previous empirical and statistical methods, the proposed method can also incorporate other types of data, such as geological data and fluid properties. The method can be applied in multiphase fluid situations and, since it is simulation based, it provides a platform for easy transition to more detailed analysis. Thus, the method can serve as a valuable reservoir management tool for operators of stripper oil fields.

DEDICATION

To my parents Luis Eladio and Vitalia, who have offered me unconditional love and support throughout my entire life.

ACKNOWLEDGMENTS

I am grateful to all those who have contributed to this thesis, especially to my advisor, Dr. D.A. McVay, for his wise guidance and to Quicksilver Resources for providing the model data set of Cut Bank field and for giving permission to use it in my thesis.

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INTRODUCTION

Quantifying redevelopment potential in marginal oil and gas fields is often difficult. Many oil and gas fields have resources that will not be recovered with existing development plans. Challenges include high vertical and areal variability in rock quality and connectivity, variable completion and stimulation practices, inconsistent well spacing, incomplete well histories and inadequate databases for reservoir characterization.

Additionally, producing fields may be large, containing numerous wells. The most accurate method for identifying opportunities in such fields is to use a detailed, integrated reservoir model based on geophysical, geological and engineering data and interpretations. Such models require detailed databases, geological model development, reservoir property estimation, simulation model construction and calibration, and finally, using the model to optimize reservoir performance. Automatic history matching tools have been developed over the past few years to help the petroleum engineer achieve a history match between a simulation model and the corresponding observed reservoir data. However, despite automatic history matching tools, integrated studies are prohibitively time-consuming and expensive for marginal oil and gas fields, and they are impractical for independents with limited staff. In addition, there are often insufficient data for these studies. Hence, there is a need for less-demanding methods that characterize and predict heterogeneity and production variability.

As an alternative approach to conducting detailed studies, various authors have used empirical or statistical analyses to model variable well performance.[1-5] Many are based solely on well location, production and time data. Mosaic Technology[4] is an advanced technique that uses a model-based 4D regression of production vs. virgin productivity,

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This thesis follows the style and format of the *SPE Journal*.

cumulative production, and well spacing. A field is evaluated not as one single study, but as a mosaic of overlapping local studies. The Mosaic technique employs model-based analysis in each moving window. The model is based on a combination of the material balance equation and the pseudosteady state flow equation, simplified by assuming that many properties are constant within an individual window. The final reservoir description is location-dependent, allowing both large-scale and small-scale trends to be identified. Once the regression equation coefficients are determined for each window, performance can be estimated for infill wells by substituting the appropriate values for candidate infill well conditions. The result of this analysis is a prediction of production rate potential for a new well offsetting each existing well. Results are approximate, due to the assumptions inherent in the procedure, although still useful. As reported by Guan *et al.*,[4] Mosaic analysis can reliably determine the infill potential for groups of wells, often to within 10%. However, individual well predictions can be off by 30% to 50% in some cases. Thus far, the technique has been used mainly for primary depletion problems. Other limitations are that it is hard to incorporate other types of data and it does not handle easily multiphase situations.

The Albertoni and Lake method (AL)[5] is another alternative technique to conventional reservoir studies developed to quantify communication between wells (injectors and producers) in a reservoir. The technique, which uses only production and injection rate data, combines a constrained multivariate linear regression analysis with diffusivity concepts to provide information about permeability trends and the presence of transmissibility barriers. The AL technique calculates the fraction of flow in a producer attributable to flow at an injector. The analysis is performed on a field-wide or regional basis, and analyzes multiple well influences in a single step. It uses filters to account for the time lag and attenuation occurring between each injector-producer pair. The technique provides information about permeability trends and the presence of transmissibility barriers. While it indicates heterogeneity, it does not provide quantitative information with respect to infill drilling.

As an alternative to Mosaic and other moving window methods, Gao and McVay[6] have been investigating the use of reservoir simulation combined with automatic history matching to rapidly assess infill-drilling potential in unconventional gas reservoirs. As described above, the Mosaic method combines the material balance equation with the pseudosteady state flow equation in a 4D regression of production data within each moving window. A reservoir simulator also combines material balance equations with flow equations, albeit with more rigor. The approach used by Gao *et al.* is to use reservoir simulation combined with automatic history matching to regress production data, similar to the Mosaic approach. The difference is that they regress, or invert, production data to determine the permeability distribution on a cell-by-cell basis. Then, they use the permeability distribution and an array of automated simulation predictions to determine infill drilling potential throughout the reservoir. The methodology is based on inverse theory and it uses primarily well locations and production data. It can incorporate available geological information, but a reservoir characterization study is not required. Accordingly, the results are only approximate. Thus far, it has been applied only to single-phase problems.

After reviewing the alternative approaches to conventional reservoir studies, there is still a need for methods to quantify infill potential that are rapid and cost-efficient, but reasonably accurate, that would be applicable to waterflooded oil reservoirs such as the Cut Bank field. Cut Bank field is located in northern Montana and has been under water injection for approximately 40 years. This data set was used to test the proposed methodology to quantify infill potential.

The research objectives were to:

- Develop improved methodology for rapid assessment of redevelopment potential in marginal oil fields. The improved method should provide for the incorporation of other data types, such as seismic data. In addition, it should be applicable to multiphase flow, such as in waterflooded oil reservoirs.

- Test the methodology in synthetic cases and in an actual marginal oil field, the Cut Bank field, to establish its applicability and limitations.

The proposed methodology uses reservoir simulation combined with automatic history matching tools. The software that I use for automatic history matching is the commercially available software SimOpt[7], from the Eclipse suite for reservoir simulation, developed by Schlumberger. This tool relies on efficient computation of sensitivities of production responses to reservoir parameters and use of a regression algorithm to optimize the objective function.

Three tests of the methodology are presented. The first one in a single-phase synthetic case, the second one in a multiphase synthetic case derived from Cut Bank field and the third one with the actual data set of Cut Bank field. An overview of Cut Bank field is presented describing the geological features and other general information of the field.

METHODOLOGY OF NEW APPROACH

The proposed methodology uses conventional simulation combined with automatic history matching tools to establish the infill potential of an oil field. I regress production data to determine the permeability distribution and then use this permeability distribution to determine infill drilling potential throughout the reservoir using an automated procedure. The methodology provides the ability to work in multiphase situations such like waterflooded reservoirs and the permeability match is region-based, rather than cell-based.

A likely objection to this proposed approach is that, since it is based on reservoir simulation, it will require a complete reservoir data set. The complete reservoir data set will either not be available or will require a reservoir characterization study, which will increase the times and costs significantly and which will provide no advantage over conventional reservoir studies because it will be, in fact, just like any other reservoir study. This is not the case here.

My objective is still rapid assessment of infill-drilling potential using only readily-available well locations and production data, thus providing approximate, statistical assessments for significantly less times and costs than conventional reservoir studies. To accomplish this I adopt several strategies. First, I do not conduct a reservoir characterization study. For data other than well locations and production data, I use only what are currently available. Second, I use relatively coarse simulation grids, by conventional simulation standards, and fewer layers (often only one) to minimize run times and costs and to reduce the number of parameters in the regression. Third, I use different regression parameters than I use in conventional reservoir simulation studies. Instead of matching on individual cell values of reservoir properties (usually permeability), I match on constant values of permeability within the Voronoi regions around each well. Thus, the number of regression parameters is reduced to the number of wells. Fourth, I use different well controls and matching variables. In conventional reservoir simulation history matching, we usually fix the production of the primary hydrocarbon phase and match on reservoir pressure and production ratios, such as GOR and WOR. In the application of my proposed approach to marginal reservoirs, we often have no reservoir pressure data. Thus, I control the wells using an estimated constant flowing bottomhole pressure and match on production rates. Using a reservoir simulator in an approximate way like this requires a change in mindset, which may be difficult for some engineers. Because of the assumptions and approximations I make, the results are approximate. Thus, with this approach, in essence, I am using the reservoir simulator as an approximate, statistical tool.

There are a number of advantages to this simulation-based approach. First, it does not require the assumption of uniformity of reservoir properties in windows of 5 to 20 wells, as does the Mosaic method. Second, since it utilizes a reservoir description instead of simplified regression equations, seismic data and other types of geological information can be more readily incorporated than in moving window methods. This should improve the quality of the results and decrease the level of uncertainty. Third, the approach provides a means for gradual transition from preliminary scoping studies to more rigorous, conventional reservoir studies. As more data and interpretations are acquired, the model reservoir description can be updated and the regression repeated, increasing the accuracy of predictions using the simulation model. Mosaic and other moving window methods do not provide an easy means for transitioning to more rigorous analyses. Finally, the method can be more-readily applied to marginal oil fields, such as the Cut Bank field, than moving window statistical methods, since reservoir simulators are already capable of modeling multiphase flow.

The proposed methodology has several steps that are described below.

1. First, I build a simulation model of the field. I use accurate information regarding well locations and well production and injection data. As for geological information, such as horizon depths, isopach, porosity and permeability maps, I use only what are currently available. For example, if a net thickness map is available, I input it into the simulator; otherwise, I use an estimated average value of net thickness. PVT data and relative permeability information are also incorporated in the model, if available; if not, correlations are used instead.

2. Define what property we are going to match during the regression (permeability in our case) and the Voronoi regions (region of grid cells closer to a well than any other well) around each well where permeability is going to be modified.

3. Decide which well controls are going to be used during the regression and what observed data is going to be matched. I control the wells using an estimated constant flowing bottomhole pressure and match on production and injection rates.

4. Perform the regression using SimOpt. The regression works as a loop that iteratively tunes the parameters to match simulated data to the given observed data. First it makes a forward run to establish the difference between the simulated data and the observed data, which is part of the objective function. Then, it calculates sensitivities of simulation quantities (for example oil production from a well) with respect to variations in the simulation model input data (parameters) using gradients calculated by ECLIPSE 100 in a single run. Calculating the gradients increases the time taken to run the simulation by about 20% per parameter, but is still much faster than making multiple runs to calculate these sensitivities manually.[7] Finally, it performs the inversion to minimize the

objective function. As an outcome of the regression we will have a permeability field that gives the best history match of the simulation model. Further details on how SimOpt works are provided below.

5. The fifth and final step is to determine the infill potential. To determine infill-drilling potential, I make performance predictions with the reservoir simulation model and the permeability distribution resulting from the regression of production data. I first make a base case forecast in which we continue current operations, and then record the ultimate recovery. To determine the potential incremental recovery to be realized from drilling an infill well at a particular location, I make a projection for the same time as the base case in which I drill and produce one new well at the location (grid block) of interest, and then record the incremental recovery to be attributed to the drilling of this well. I then repeat this procedure for every grid block, using an automated procedure, to determine the incremental recovery to be realized from an infill well drilled at all possible locations (grid blocks) in the reservoir.

Technical Description of SimOpt

A key component of my proposed method is robust automatic history matching technology. I have elected to use SimOpt[7] in my methodology. SimOpt uses mathematical techniques to vary specified reservoir parameters (permeability, in my case) to minimize the difference between observed and simulated production data. It can also take into account prior geological information, when available, in the regression.[8]

The objective function, f, that is minimized in SimOpt is a modified form of the commonly used simple sum-of-the-squares.

$$f = f_{prior} + \frac{1}{2}\sum_{d,i} r_{di}^2 \quad \ldots\ldots\ldots\ldots \quad (1)$$

where

f_{prior} is the objective function prior term, which accounts for the knowledge of the statistical distribution of parameter modifier values.

r_{di} is the weighted difference between an observed value and a simulated one, which is defined as

$$r_{di} = w_d w_{di} \frac{(o_{di} - c_{di})}{\sigma_d} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2)}$$

where

d references one set of observed data of a given type at a given well

i references an individual data point for the d'th item of observed data

o_{di} and c_{di} are the observed and calculated values, respectively

σ_d is the measurement error for the d'th data set

w_d is an overall weighting for the d'th data set

w_{di} is a weighting for the i'th data point of the d'th data set

The algorithm that SimOpt uses to minimize the objective function is the Levenberg-Marquardt, which is a combination of the Newton method and a steepest descent scheme. Denoting the vector of current parameter normalized modifier values as v^k, then the algorithm estimates the change, dv^k, required to minimize the objective function as

$$dv^k = (H + \mu I)^{-1} \nabla f(v^k) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3)}$$

where the Hessian matrix, H, is the matrix of second derivatives of f and I is the identity matrix. The parameter μ is free and is varied so that, away from the solution where the quadratic Newton model may have less validity, it takes large values and biases the step towards the steepest descent direction. While near the solution, it takes small values to make the best possible use of the fast quadratic convergence rate of the Newton step.

In solving Eq. 3, SimOpt requires the first and second derivatives of the objective function (Eq. 1) with respect to the normalized parameter modifiers. SimOpt recommends using no more that 50 parameters in the regression. The first derivatives are the components of the gradient vector of the objective function,

$$[\nabla f(v)]_j = \frac{\partial f}{\partial v_j} = -\sum_{d,i}\left(\frac{w_d w_{di}}{\sigma_d}\right)\frac{\partial c_{di}}{\partial v_j} + \frac{\partial f_{prior}}{\partial v_j} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (4)$$

The second derivatives are the components of the Hessian matrix of the objective function,

$$[H]_{jk} = \frac{\partial^2 f}{\partial v_j \partial v_k} = \sum_{d,i}\left(\frac{w_d w_{di}}{\sigma_d}\right)^2\left(\frac{\partial c_{di}}{\partial v_j}\frac{\partial c_{di}}{\partial v_k} - [o_{di} - c_{di}]\frac{\partial^2 c_{di}}{\partial v_j \partial v_k}\right) + \frac{\partial^2 f_{prior}}{\partial v_j \partial v_k} \quad \ldots\ldots \quad (5)$$

It is common to ignore the term involving second derivatives of the simulated value in Eq. 5; this is the Gauss-Newton approximation. A justification for this is that it is frequently small in comparison to the first term. Also, it is premultiplied by a residual term, which is small near the solution, although the approximation is used even when far from the solution. Thus, the problem can be solved with first derivatives of the simulated quantity with respect to the parameters. These derivatives are obtained from the run of Eclipse 100 at the same time as the simulated quantities themselves, and in just one run.

SimOpt expresses the overall measure of the history match as a Root Mean Square (RMS) index formed from the regression objective function:

$$RMS = \sqrt{\frac{2f}{m}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (6)$$

where m is the total number of observations over which the index is formed, and f is the objective function. This RMS index provides an average value of the deviation between simulated and observed data.

TESTS OF METHODOLOGY ON SYNTHETIC CASES

Single Phase Synthetic Gas Reservoir Case

I first tested the methodology on a single-phase gas reservoir synthetic case. A single-phase problem was a good start for evaluating the methodology since it does not involve as many variables as a multiphase case. A synthetic case from the work done by Guan *et al*.[4] to quantify the accuracy of the moving window technique was used to test the proposed approach. They generated random permeability fields using a log-normal distribution. The simulation model was defined on a 54x54x1 grid. The distribution I used to generate the observed data for my synthetic case had an average permeability of 0.2 md and a standard deviation of 0.06 md (Fig. 1). The model had 100 wells starting production at different times over a 40-year period, representing several rounds of infill drilling. It used realistic well spacing and the wells in the model were constrained by bottom hole pressure. Other general characteristics of the model are listed in Table 1.

Table 1—General Characteristics of Single Phase Gas Synthetic Model

Porosity, %	7.2
Initial reservoir pressure, psia	1,100
Flowing bottom hole pressure, psia	250
Well bore radius, ft	0.354
Initial water saturation, %	40

The model had uniform porosity, depth and thickness. Fig. 1 shows the permeability map and well locations. I ran the simulation model to generate the synthetic observed data, which consisted of gas rates. SimOpt offers the capability to use the sensitivities calculated by Eclipse 100 to indicate regions (gradzones) for a specific parameter that will give good regression performance. SimOpt assumes that a small number of parameters are defined. I tried this option to determine regions for permeability and

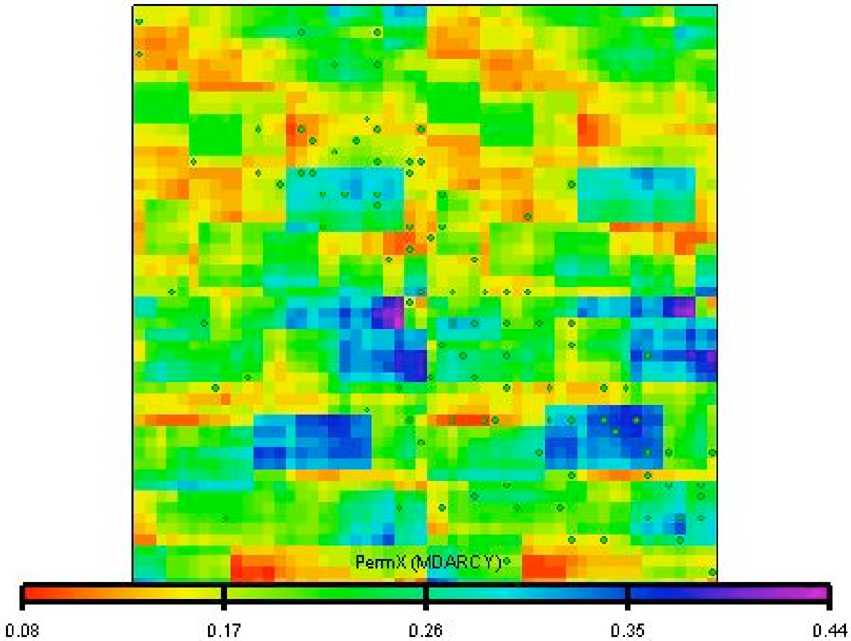

Fig. 1—Permeability map used to generate observed data

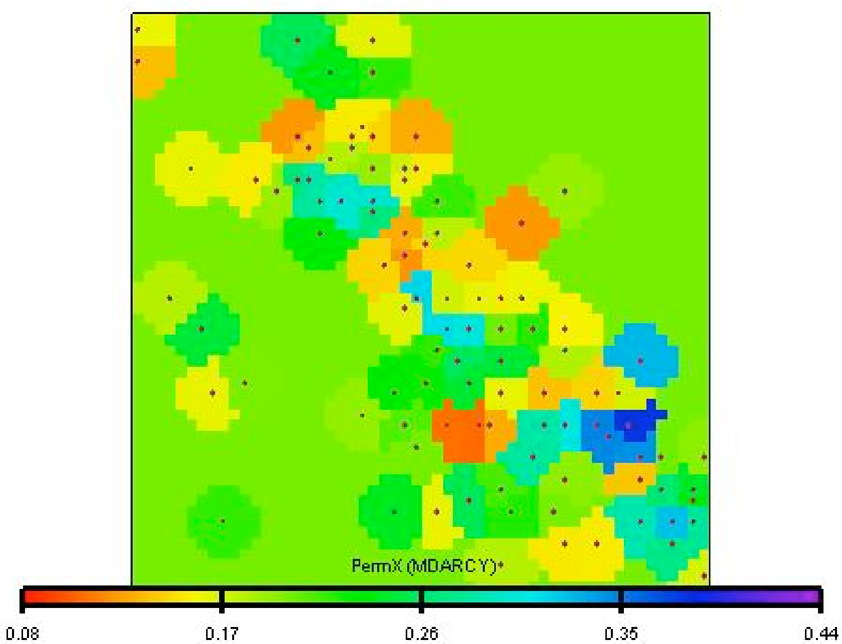

Fig. 2—Resulting permeability map after regression

six gradzones were defined for the model; however, the match did not improve during the regression. I then decided to use Voronoi regions around each well to obtain a permeability field with higher resolution that would describe better the heterogeneity of the reservoir. I ran the regression using SimOpt, matching on the uniform permeability values in the Voronoi region surrounding each well, resulting in one matching parameter per well. The regression was started with a uniform permeability value of 0.2 md. Fig. 2 shows the permeability field resulting from the regression. The map does not replicate exactly the original one, because the regression is performed on regions, rather than on a cell-by-cell basis. Also, the Voronoi regions do not cover the entire domain because a maximum radius around each well was used when the Voronoi regions were defined. However, the regressed permeability field resembles the heterogeneity of the known permeability field in the areas where permeability was matched. The regression converged in 35 iterations with the major improvement of the objective function obtained within the first 15 iterations (Fig. 3).

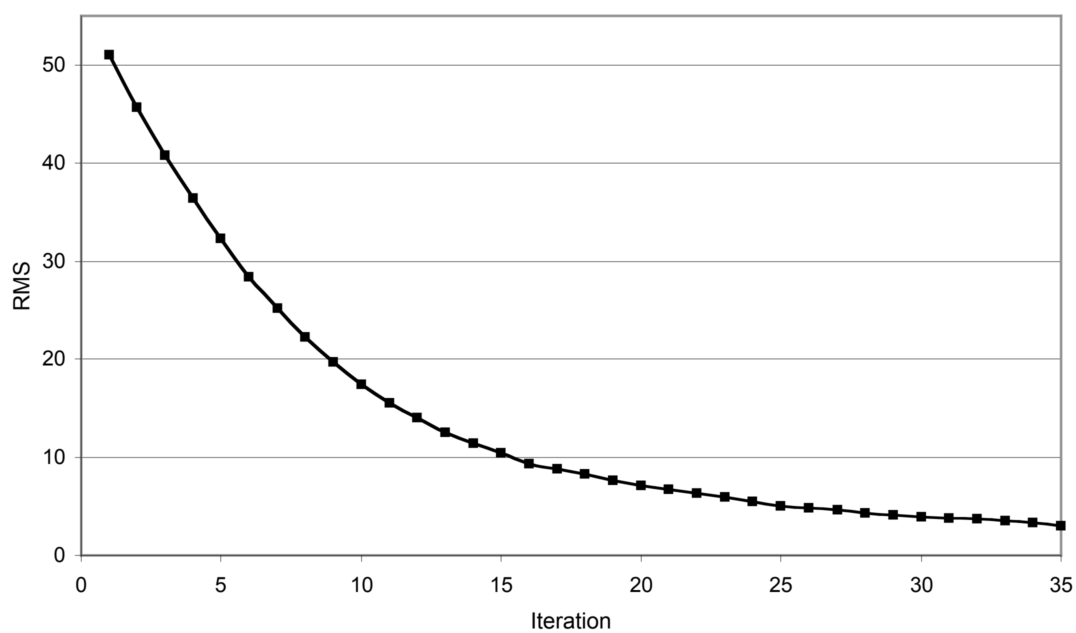

Fig. 3—Regression converged after 15 iterations

CPU time per iteration was 8 minutes on a PC machine. The match between observed and simulated data is excellent, as can be seen in Fig. 4, for the best and worst well matches, which were selected based on the RMS index. Fig. 5 shows the match on a field wide basis and Fig. 6 shows a very good match for a well that starts producing early in the history of the synthetic model.

Infill potential was evaluated with the regressed permeability field and with the known permeability field used to generate the synthetic observed data. Comparisons of these results along with the infill predictions using Mosaic technology are shown in Table 2. Mosaic makes predictions of G_p, which is the best 12 consecutive months of production divided by 12 for a new infill well offsetting each existing well.[4] Infill calculations from simulation were converted from a cell basis to a well basis to compare with Mosaic results. Table 2 shows maximum new well cumulative production (G_p) in each well's Voronoi region and the arithmetic average of new well G_p over all the cells in each well's Voronoi region. Predictions for 100 potential infill wells show that the proposed technology is more accurate than the moving window technique.

Table 2—Infill Prediction Comparison

Average New Well Cumulative Production (G_p)	Calculated from reference permeability	Calculated from mosaic	Calculated from regressed permeability
Average, m^3/month	564	517	540.86
Max, m^3/month	962	873	810.27
Min, m^3/month	354	199	368.92
Standard Deviation	137.64	149.52	93.65
Relative error (%)	-	-8.333	-4.10

The single-phase gas synthetic case allowed me to become familiar with the commercial history-matching software and to evaluate its capabilities on a small-scale problem. The results were promising and motivated me to continue my research with a more complex problem.

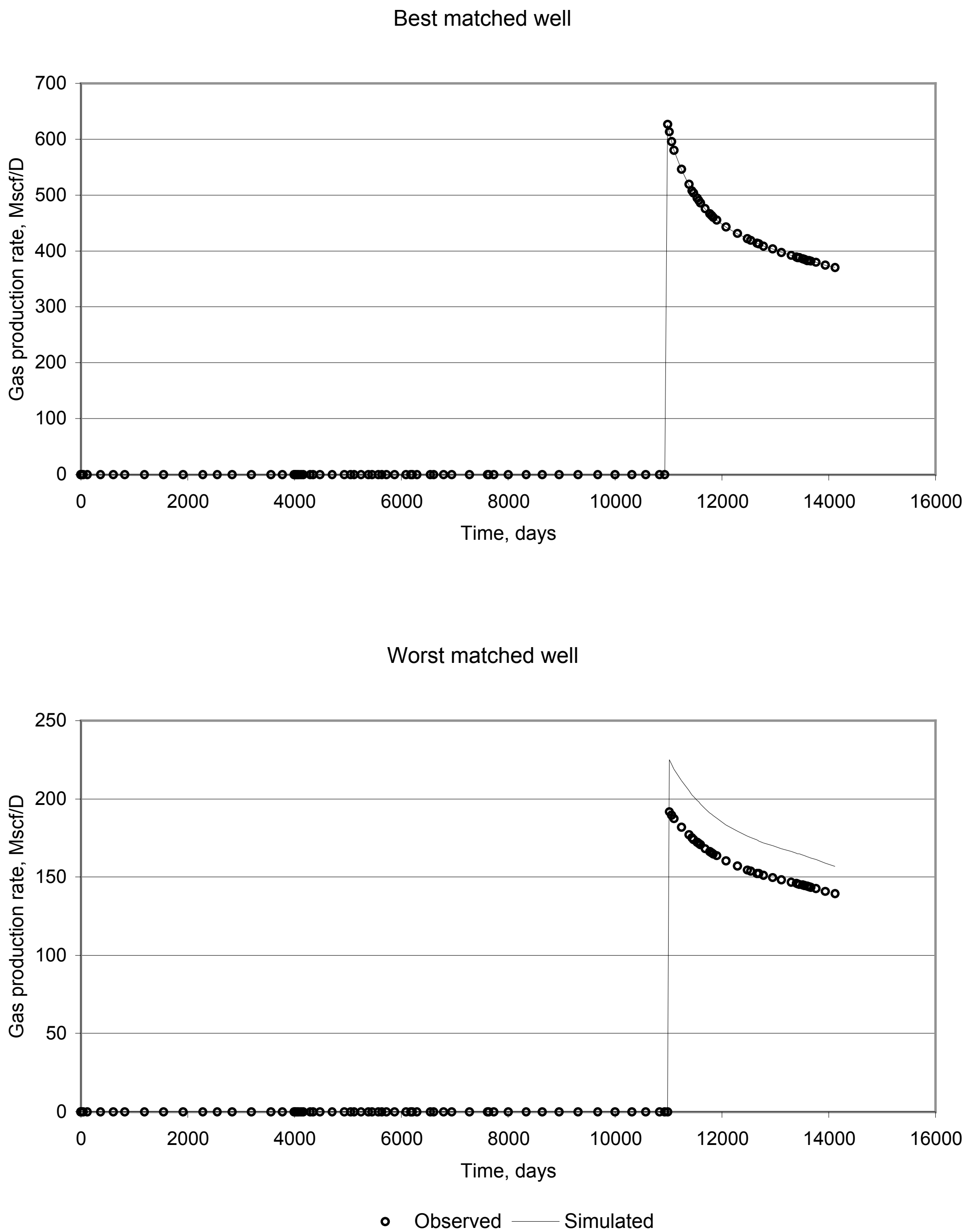

Fig. 4—Match results of single phase synthetic case

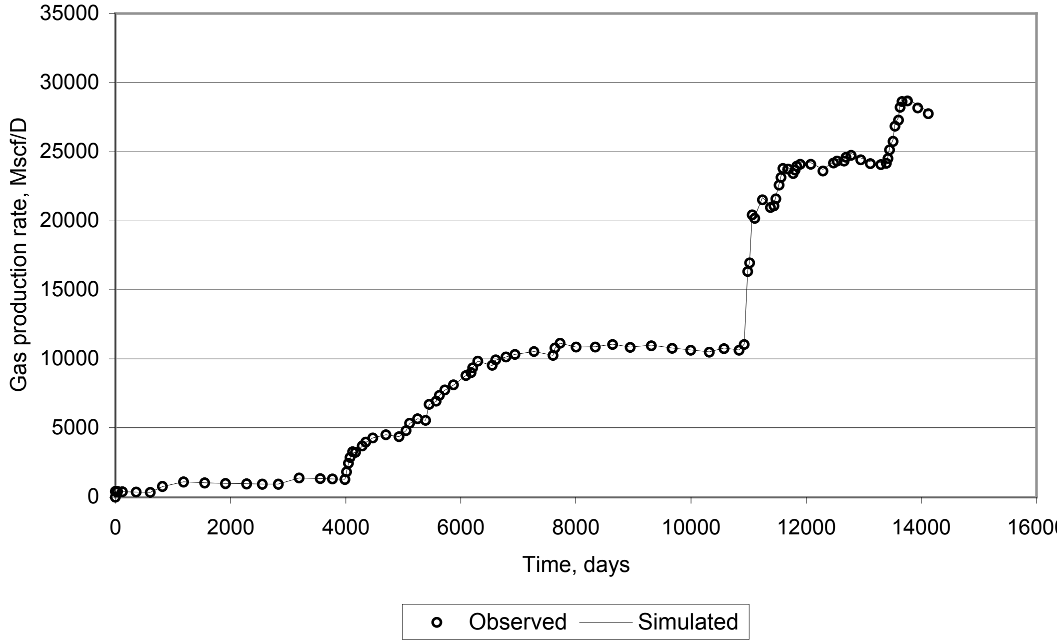

Fig. 5—Field wide match results of single phase synthetic case

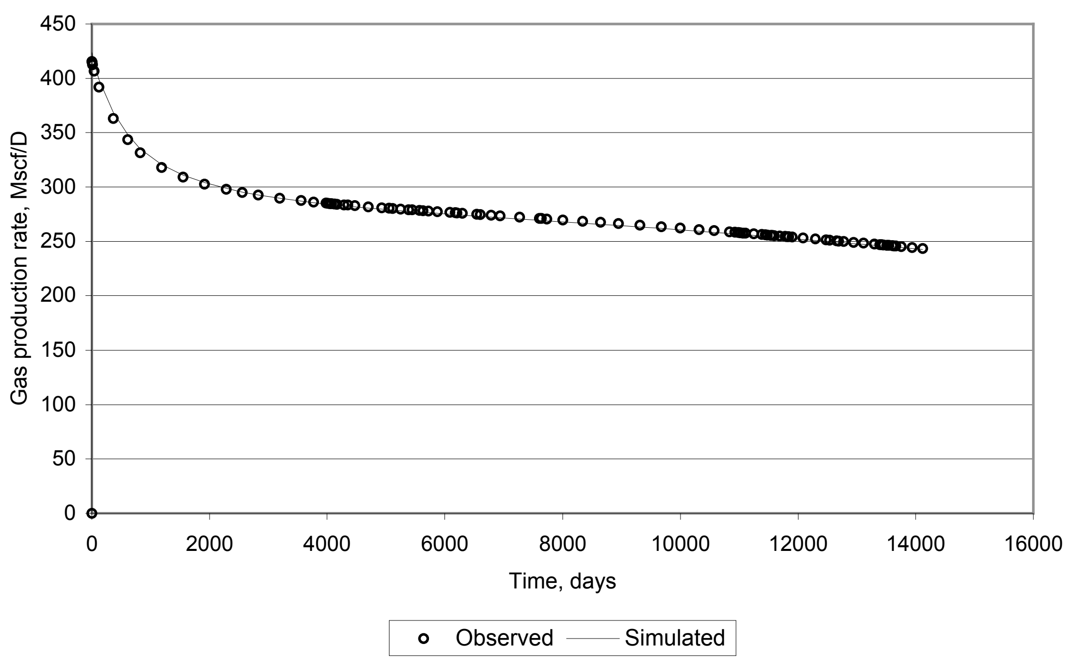

Fig. 6—Match results of a well that starts producing early in field history

Cut Bank Field Overview

Cut Bank field, located in Glacier, Pondera, and Toole Counties, northwest Montana (Fig. 7a), was discovered in 1926. The first commercial oil well was not completed until August 1931. Cut Bank oil field is a long, narrow oil-leg on the west side of a larger stratigraphic trap on the west flank of the Kevin-Sunburst Dome. Production in Cut Bank field is primarily from the Lower Cretaceous Cut Bank Sand, which is a braided-to-meandering fluvial sandstone deposit,[9-13] as shown in Fig. 7b. The oil field is 30 miles long and ranges in width from less than 2 miles near the northern end to about 6 miles near the southern end. The gas-oil contact of the Cut Bank sandstone is at approximately +1,040 ft. At the north margin of the field, the Cut Bank oil/water contact is tilted, cutting across structural contours from +1,300 to +600 ft from the west to northeast (Fig. 8). The Cut Bank Sand is comprised of upward fining sands with interbedded shales. Thickness of the unit ranges from more than 80 ft on the west to zero at the pinchout on the east. Cut Bank sandstones are generally medium- to coarse-grained litharenites in which the lithic component comprises a wide range of chert and silicified sedimentary rock fragments. On the basis of outcrop studies, Horkowitz[12] described the principal detrital constituents of the Cut Bank sandstone as quartz, silicified carbonate clasts, and argillaceous chert clasts. Chert content of the sandstone may exceed 50%.

Texture ranges from conglomerate to fine-grained sand. Porosity and permeability vary appreciably, both laterally and vertically. The highest porosity and permeability occur in medium-grained, conglomerate-free, cherty sand.[14] Because of wide variation in porosity and other reservoir properties, oil saturation is very irregular. Poor wells, and even dry holes, often offset good producing wells. The Cut Bank Sand is composed of two members, the Upper and Lower Cut Bank Sand (Fig. 9). The boundary between the upper and lower sands varies from gradational to abrupt. The lower sand is the main producing horizon. It is blanket-type sandstone that averages approximately 17 ft thick. The average porosity of the pay section of the lower sand is 14%, and permeability ranges from 10 md to 1,500 md, with the average being approximately 50 md.[15] The Upper Cut Bank sand is thinner and not as wide spread as the lower sand, and it produces only locally. Interpretation of the Upper Cut Bank sandstone is based mainly on log analysis. It is composed of fairly clean, uniform, fine- to medium-grained sand. Unlike the Lower Cut Bank Sand, a basal conglomerate is rare, and when it is present it is quite thin.

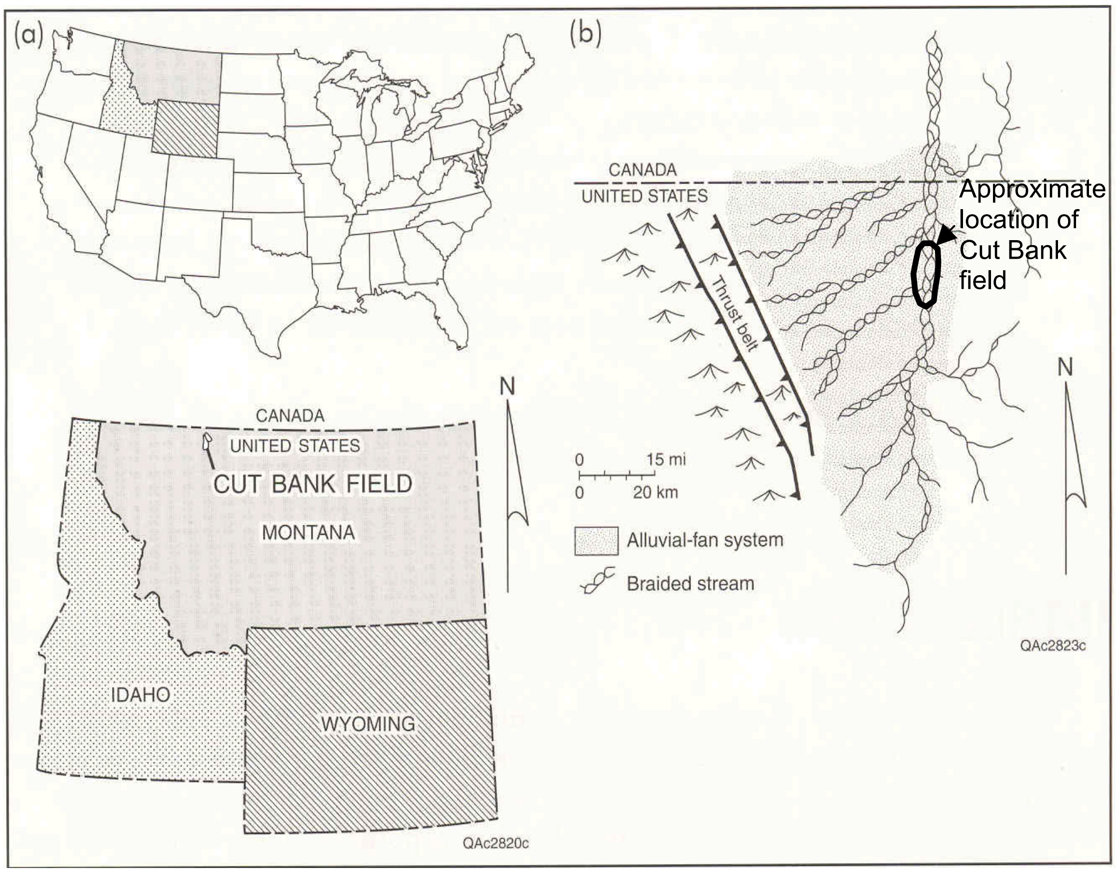

Fig. 7—a)Regional and b)depositional settings of Cut Bank field (after J.F.Treckman, MSR Exploration,[16] 1996)

Structurally, the Cut Bank field is situated on the west flank of the Kevin-Sunburst dome, and is part of a much larger feature known as the Sweet-grass Arch. The gentle

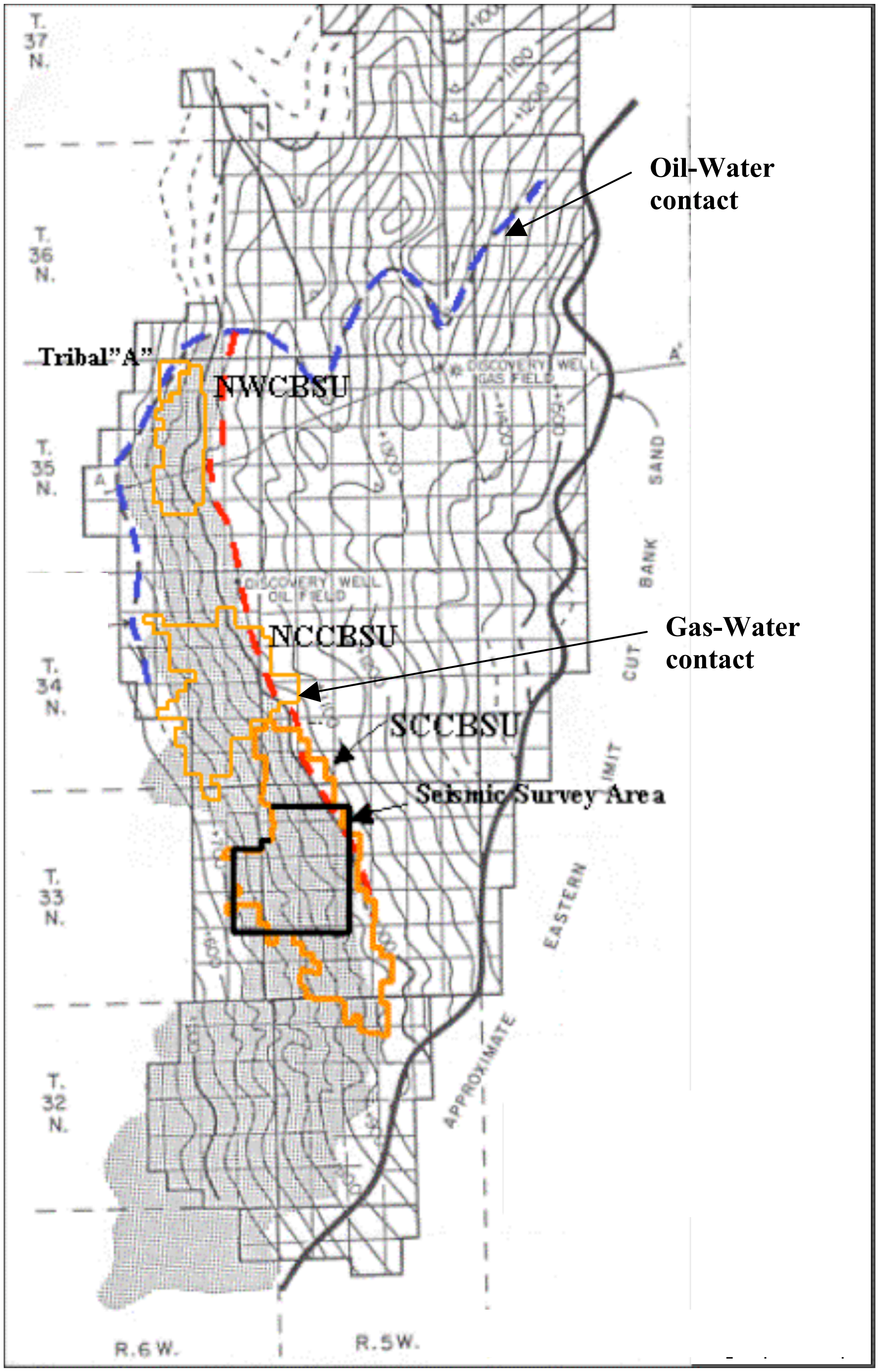

Fig. 8—Cut Bank field, generalized top of Ellis structure. Shaded area corresponds to oil leg. Outlines are Cut Bank Units and 3-D seismic survey area (Modified from Gully,[17] 1984)

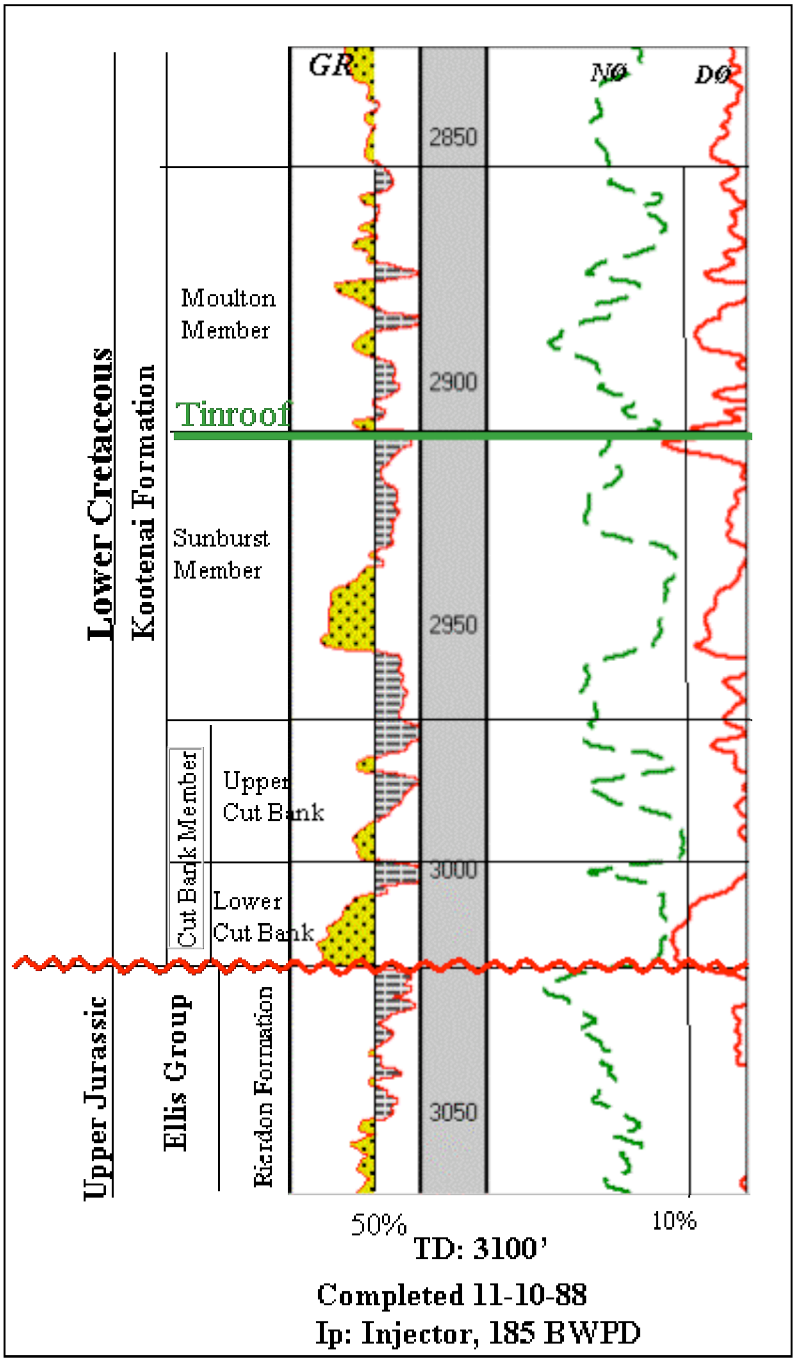

Fig. 9—Cut Bank field type log. Well SCCBSU 51-6

dip of strata on the west flank of the Kevin-Sunburst dome is illustrated by the structure of the top of the Ellis Formation (base of the Cut Bank zone) in the field area (Fig. 8). Dip is to the west-southwest at between 80 and 100 ft per mile.[14]

South Central Cut Bank Sand Unit (SCCBSU), focus of this study, produces oil from Cut Bank sands at an average depth of 2,850 ft, or +900 ft elevation above the mean sea level (Fig. 10). Fig. 8 shows the location of the SCCBSU with respect to the field. Primary production and waterflood projects in this unit have yielded approximately 43 million bbls of the 126 million bbls of oil originally in place (OOIP) in the complex, heterogeneous Cut Bank reservoir. Of the OOIP, 18.5 % was recovered by primary means. The SCCBSU water flood program was started in May 1963 and is still operating (Fig. 11).

Secondary recovery accounts for an additional 5% of the OOIP. As of July 2003, there are 277 wells in the SCCBSU area, of which 55 are active producers, 29 are active injectors, and 193 wells are idle. Daily production has declined to less than 5 STB/day in most active wells, which makes Cut Bank field a marginal field.

Production data was available on a well basis only for the last 20 years of history. I had early production data on a tract basis (1931-1963) and only total field production data between 1964 and 1982. Injection rate information was complete and on a well basis. The original reservoir pressure at the gas-oil contact (elevation approximately 1,000 ft above sea level) was about 750 psia. Reservoir temperature ranges from 78°F to 84°F.[14] Table 3 shows fluid properties of Cut Bank oil, which indicate a black oil type.

Table 3—Fluid Properties of Cut Bank Oil Show Black Oil Characteristics

API gravity	38.4
R_s, scf/STB	280
Viscosity, cp	1.3
FVF, STB/res bbl	1.13

All properties at saturation pressure of 750 psia and reservoir temperature of 82°F

In 1998, a 3-D seismic survey was acquired over an 8 sq mile area of SCCBSU (Fig. 10) to improve the ongoing waterflood program. The 3-D seismic data indicated that reservoir compartmentalization is controlled by lateral and vertical facies changes, not by faults or tectonic features.[18] Major (and some smaller) channel-fill sandstones were delineated. According to DeAngelo and Hardage,[18] the "Tin Roof" bentonite, where present, appears to dampen the seismic reflectors below it, resulting in reduced seismic clarity of the lower Cut Bank sand. Quicksilver Resources Inc. (QRI), the current operator of SCCBSU, drilled 5 new wells on the basis of the seismic interpretation. These new wells experienced oil production rates and water cuts similar to existing wells in the field, which showed rapid water breakthrough and a large ratio of water injection to fluid production. The generally poor waterflood performance is due to gravity segregation combined with generally higher permeability at the base of the Cut Bank sand.

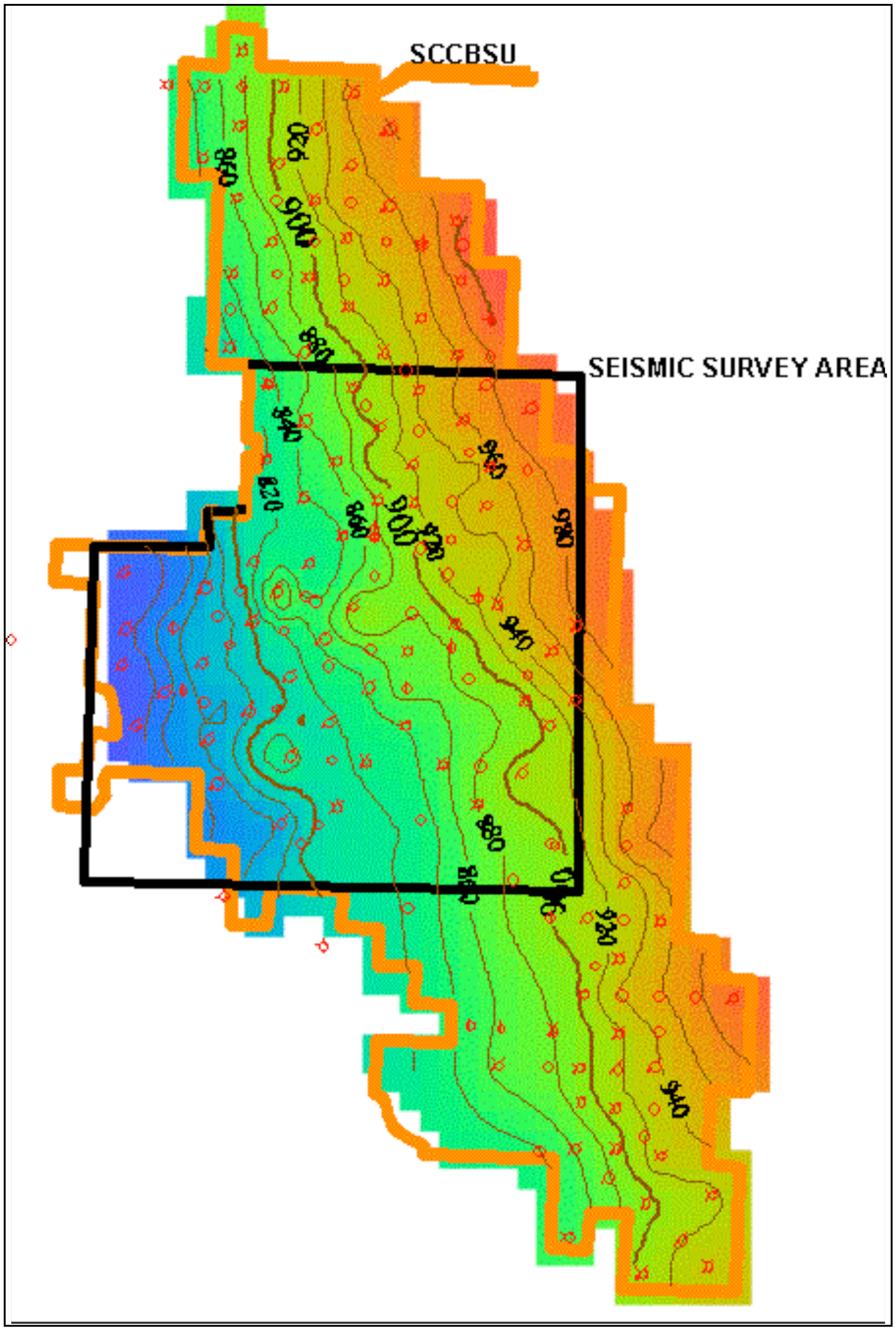

Fig. 10—SCCBSU: Structure map, top of the Ellis Group

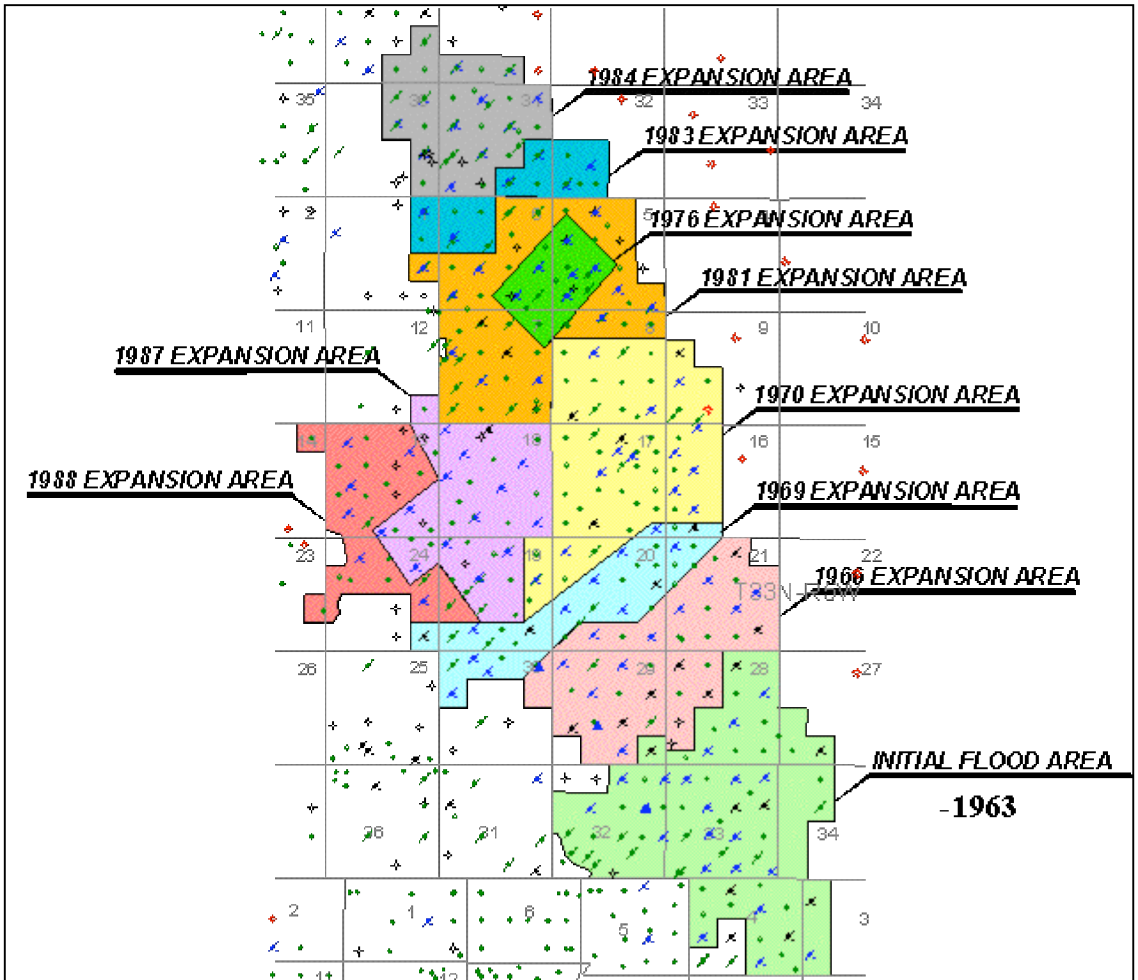

Fig. 11—SCCBSU water flood expansion history (from Quicksilver Resources[19], 2001)

Multiphase Synthetic Oil Reservoir Case

The purpose of this synthetic case was to test the methodology on a multiphase problem and to evaluate the capabilities of the commercial history-matching software. The synthetic case was derived from the Cut Bank field data set, and served as an intermediate step to implementation of the method on the actual data from Cut Bank field. To build the synthetic simulation model I used the structural map shown in Fig. 10 and the net pay map of Cut Bank field shown in Fig. 12. We used a porosity map based on log data from the field and generated a permeability map using a porosity-permeability correlation from core data. This permeability map, shown in Fig.13, became the known permeability distribution that was used to generate the “observed” production and injection data for the synthetic case. The simulation model dimensions were 80x80x1 cells.

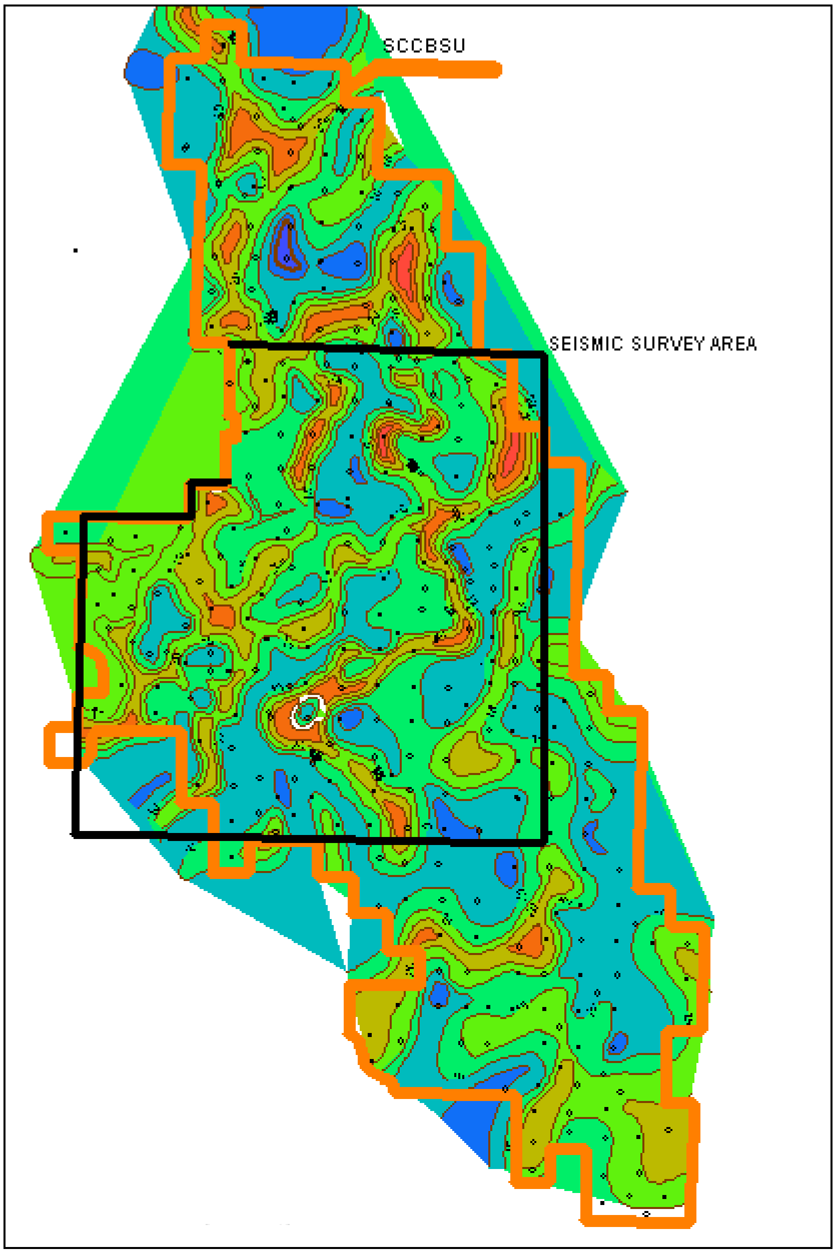

Fig. 12—Net pay map of Lower Cut Bank Sand (from Quicksilver Resources and the Bureau of Economic Geology[19])

An initial attempt to model the entire area of the Cut Bank field with the synthetic model was unsuccessful, due to the size of the problem and the limitations of the hardware I was using (PC platform). I was able to run a smaller case covering the western part of the seismic area with successful results. I moved the problem to a Unix platform to be able to run a synthetic case that would include at least the central area of the field covered by the 3D seismic survey. Our synthetic model was set to produce over a period of 20 years.

Each well in the model was constrained to produce or inject a uniform target rate value equal to the average oil production or water injection rate in its actual history. As in the single-phase case, I ran the simulation model to generate the synthetic observed data, which in this case were oil, water and gas rates and water injection rates. Then, I ran the regression using SimOpt, matching on the permeability value in the Voronoi regions around each well. The starting distribution of permeability was uniform, providing a rigorous test for the regression code. Fig. 14 shows the permeability distribution resulting after the regression, and I found that it resembles the “known” permeability field used to generate the synthetic observed data.

The RMS index decreased from a value of near 400 to 100 in 9 iterations during the regression (Fig. 15). Each iteration took 8 hours of machine time due to the size of the problem. I matched on 192 parameters, using more than three times the recommended maximum number of parameters for the software.

Figs. 16-17 show the best and worst well matches obtained between the simulated results and the observed data. Fig. 18 shows the field wide match results for oil and water rates. We consider the regression results to be good, especially given that we started with a uniform permeability distribution.

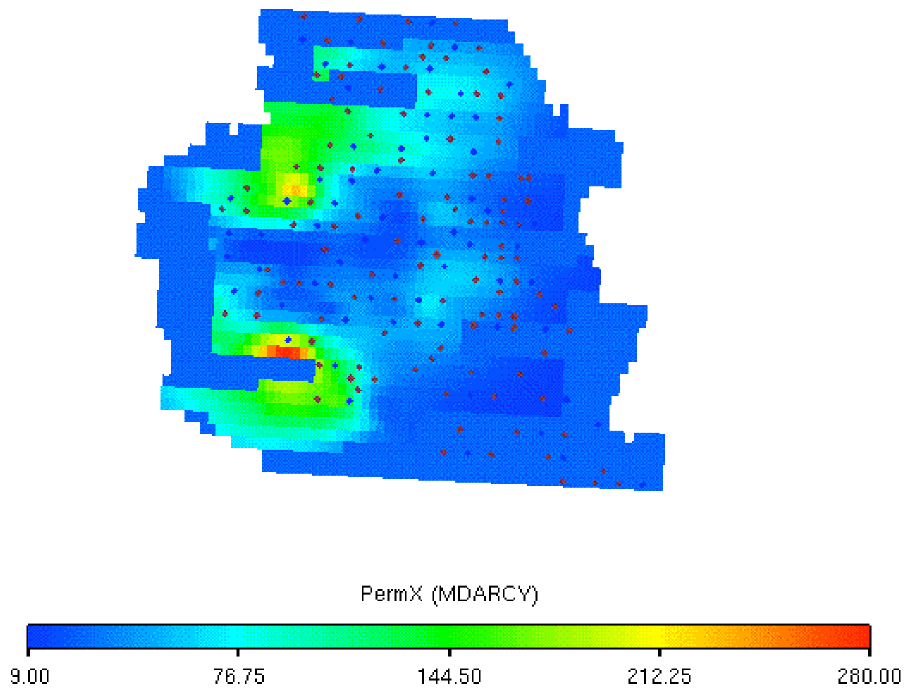

Fig. 13—Permeability map based on porosity map and correlation from core data

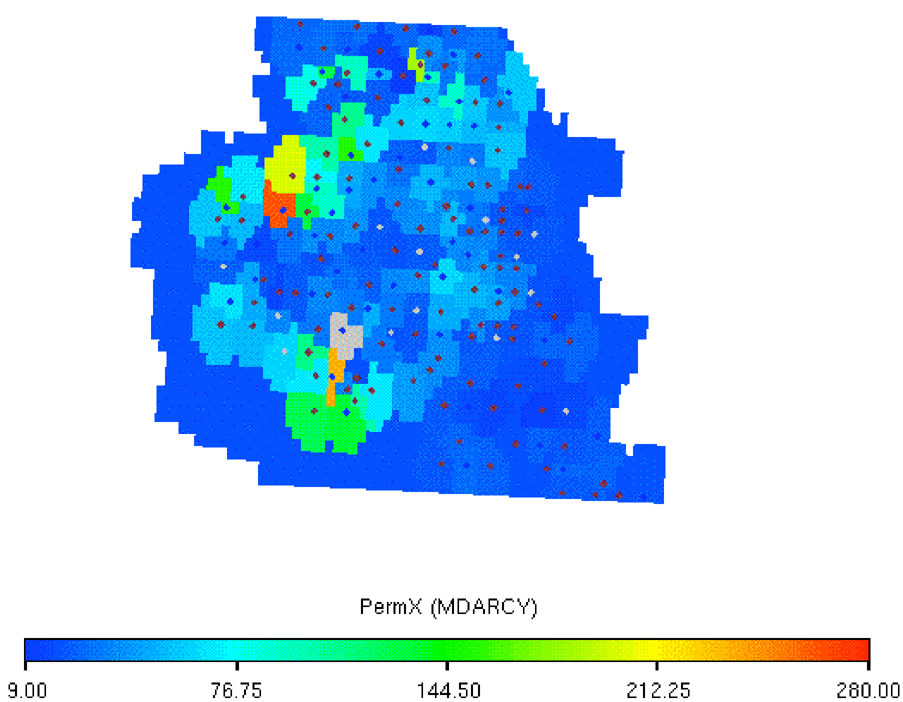

Fig. 14—Permeability map after regression

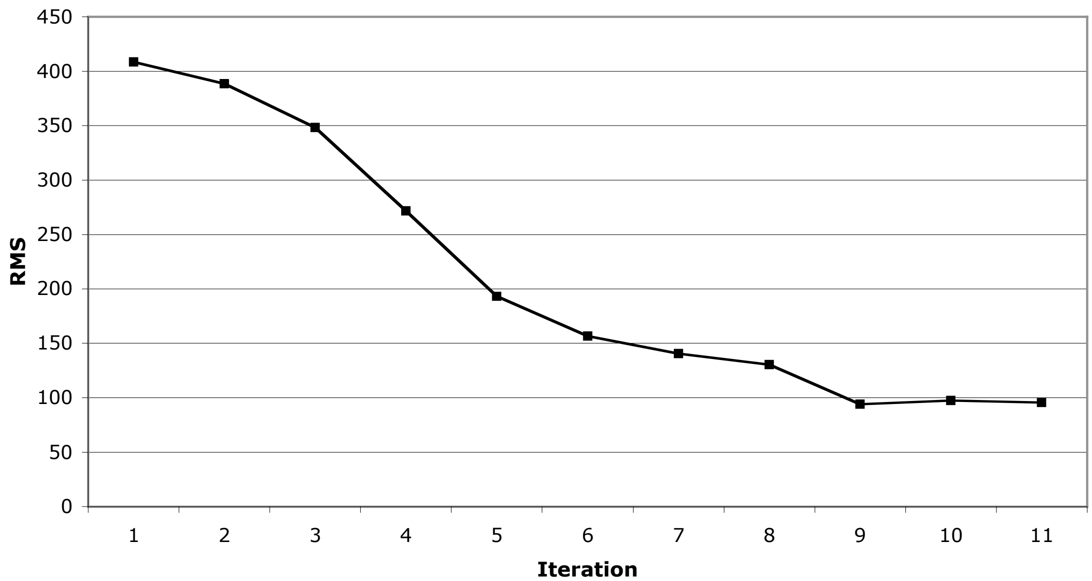

Fig. 15—Regression converged after 9 iterations

We made infill drilling predictions over a 20-year period of time. A map of infill incremental recovery is shown in Fig. 19. Visualization of infill potential in this way makes it immediately apparent that there is greater potential for infill drilling in the northwest portion of the field than in the southeast portion. These results are influenced heavily by the net pay distribution (Fig. 20) and the regressed permeability field (Fig. 14), as well as the production and injection histories. Since I have used a coarse permeability distribution in the regression (a constant permeability in the region around each well), the calculated permeability is not perfect.

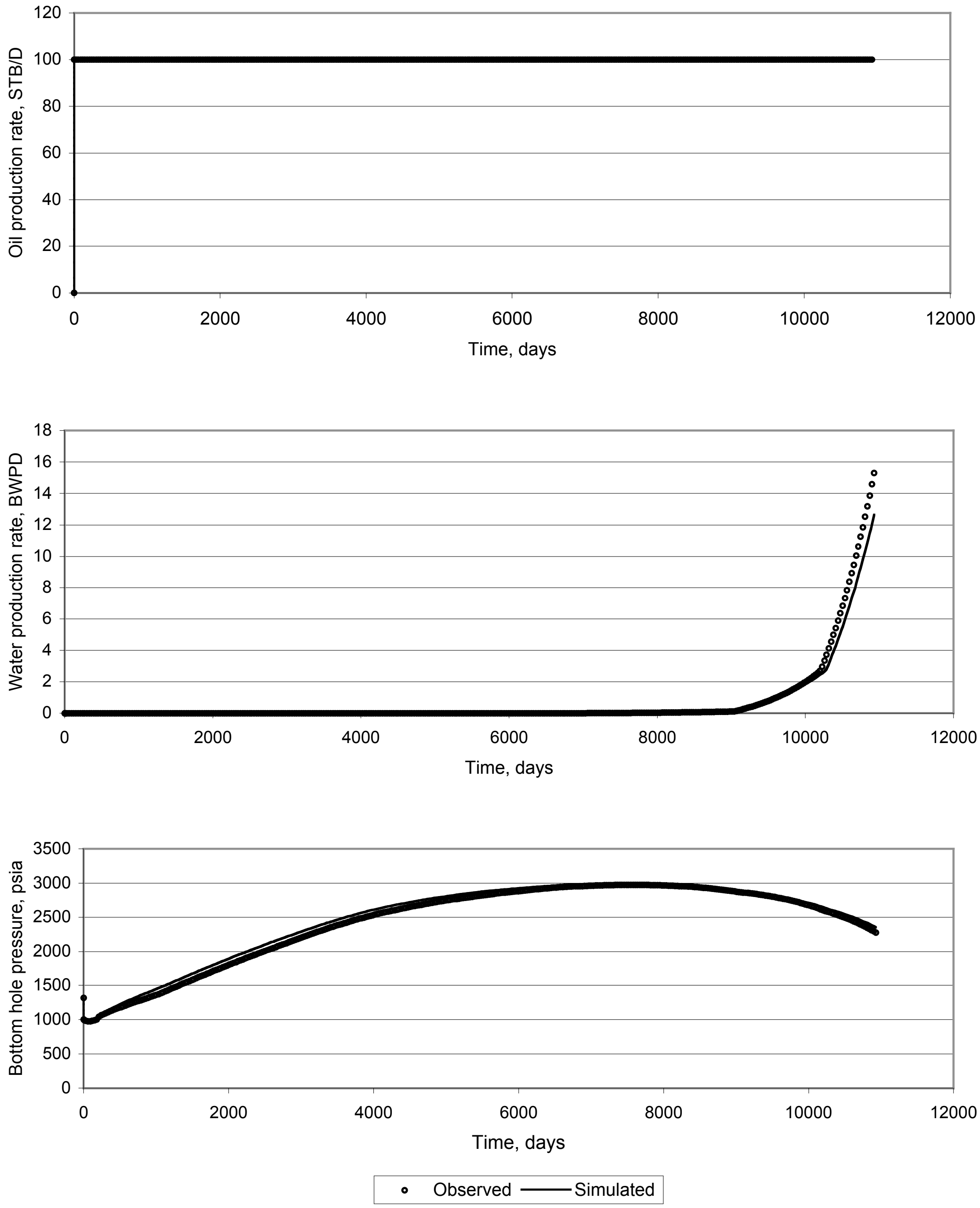

Fig. 16—Best matched well after regression

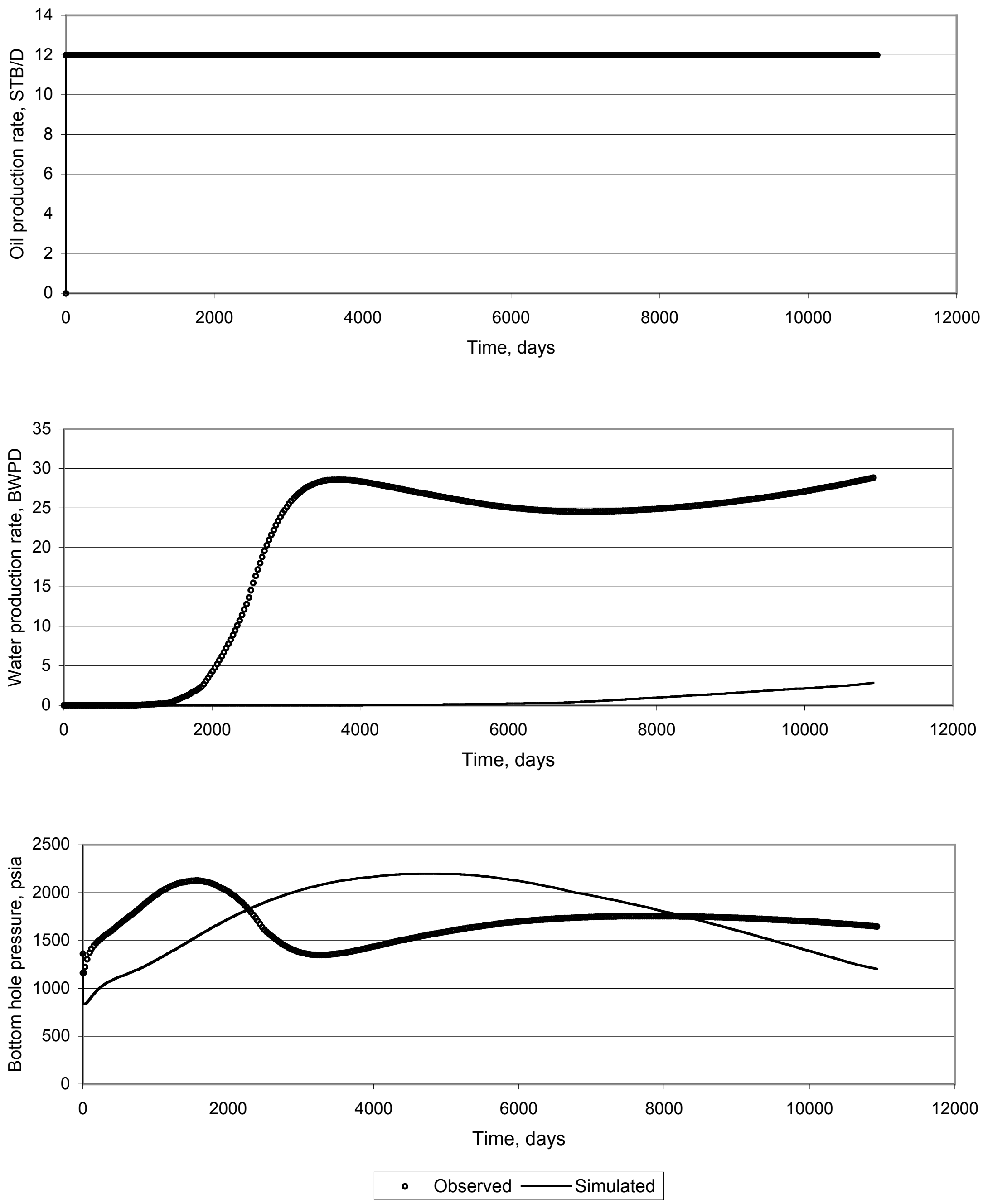

Fig. 17—Worst matched well after regression

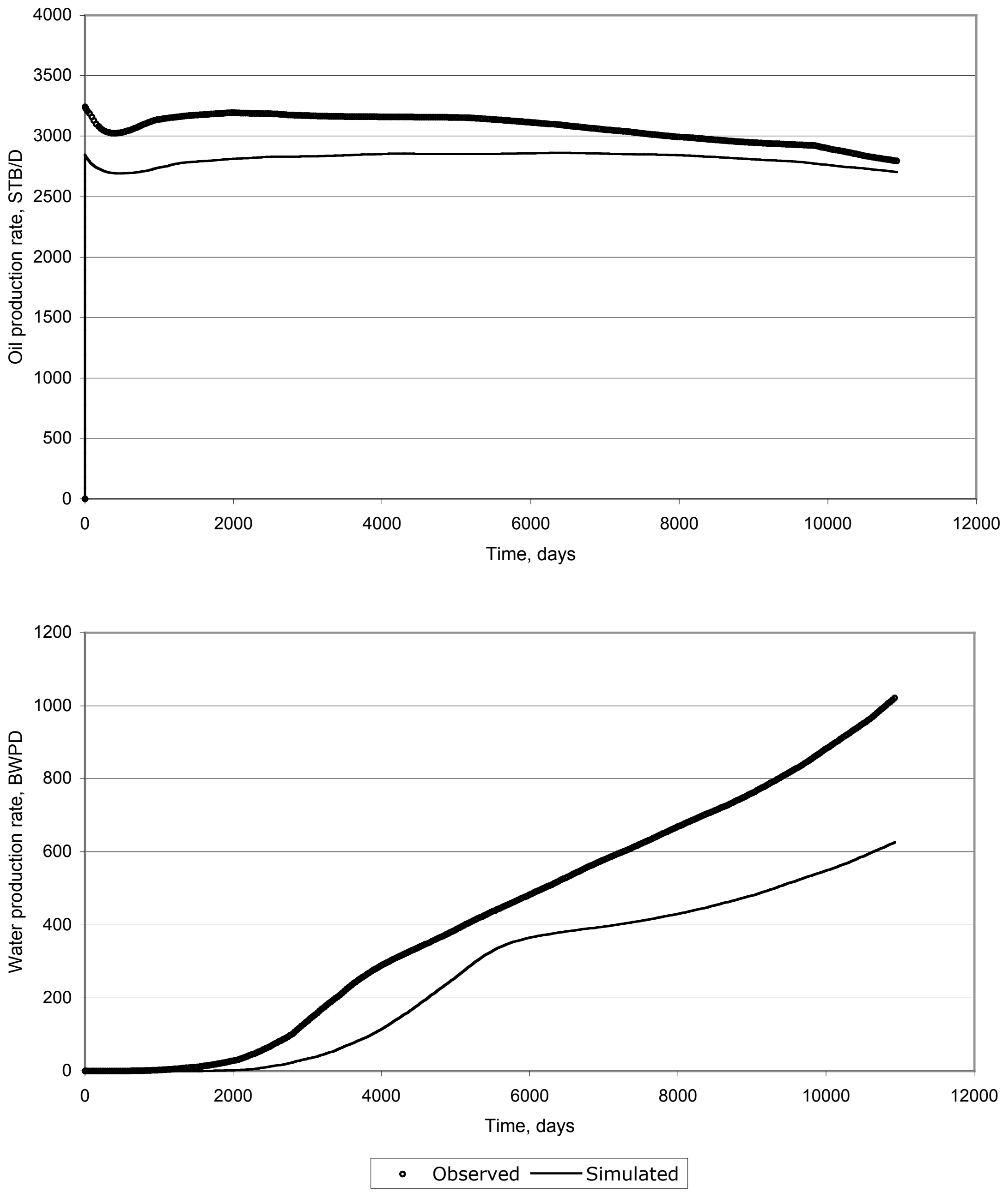

Fig. 18— Field wide match results of single multiphase synthetic case

To determine the effect of this approximate permeability distribution on the estimation of infill potential, we also constructed an infill incremental recovery map (Fig. 21) using the original, "known" permeability distribution (Fig. 13). The similarity between Figs. 19 and 21 indicates that the regionalized permeability distribution does not affect significantly the conclusions regarding which areas of the field offer the greatest infill potential.

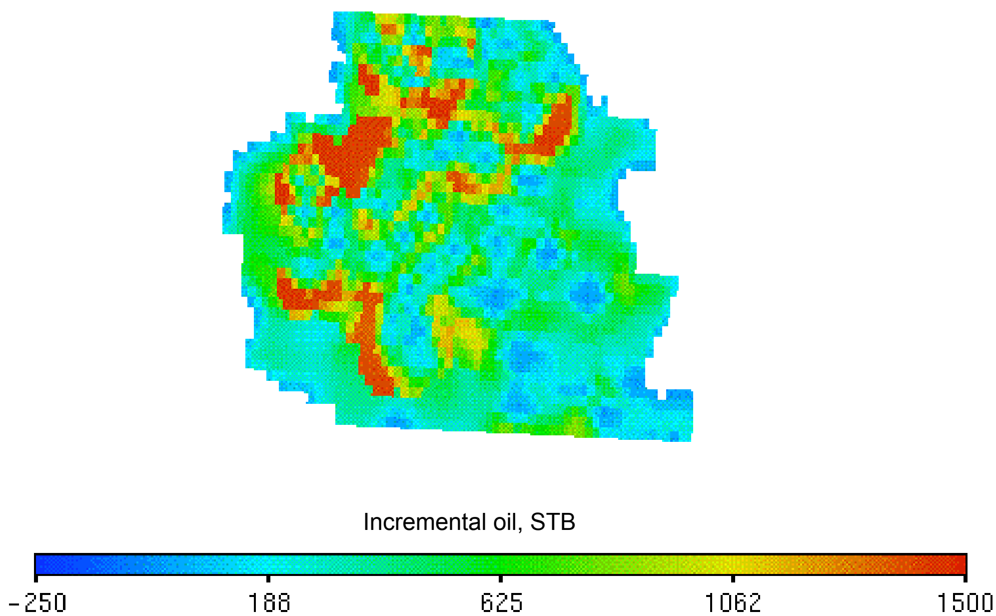

Fig. 19—Infill incremental recovery map shows potential on northwest area

Although the synthetic reservoir model was derived from the SCCBSU, the simulated production and injection performance do not necessarily closely resemble actual Cut Bank performance. In particular, the synthetic model does not experience the rapid water breakthrough, large ratio of water injection to fluid production, and low incremental waterflood recoveries that are observed in the SCCBSU.

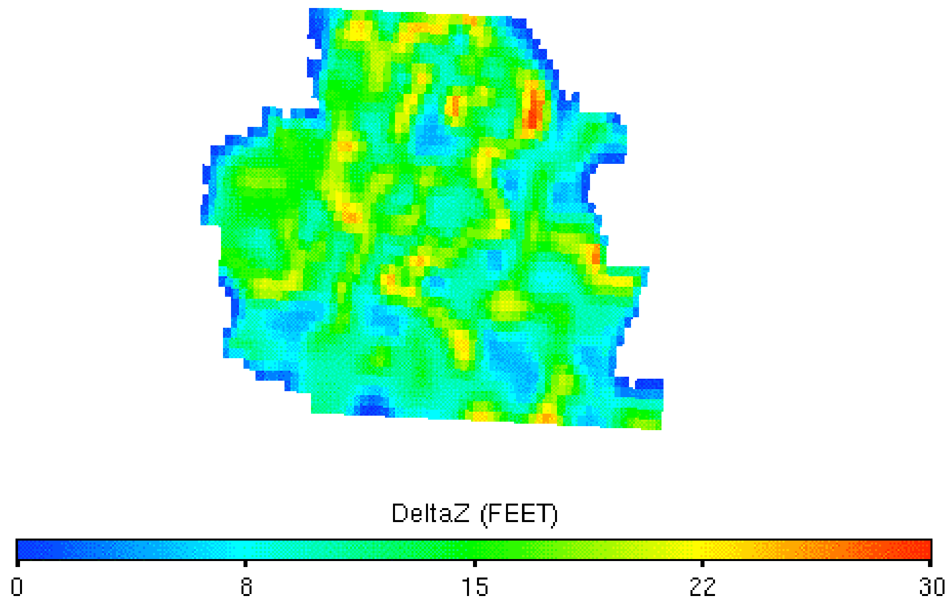

Fig. 20—Net pay map of Cut Bank field used in synthetic case

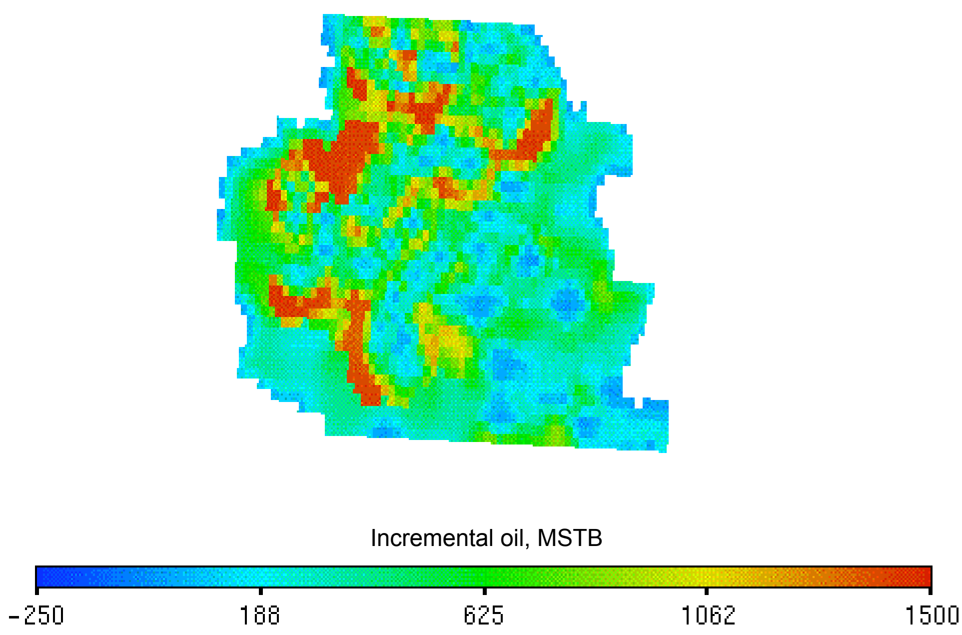

Fig. 21— Map of infill incremental oil recovery with known permeability field

We attribute these observed waterflood performance characteristics to gravity segregation combined with generally higher permeability at the base of the Cut Bank sand, neither of which are captured in the single-layer synthetic model. Nonetheless, these cases demonstrate the viability of the proposed methodology, which was the objective of the synthetic modeling.

TESTS OF METHODOLOGY ON ACTUAL CASE

With encouraging results from the synthetic case derived from Cut Bank field, I proceeded to test the methodology with the actual production and injection history of the field. The model covered the central area of SCCBSU where the 3D seismic survey was acquired, just as the synthetic case. This time, however, the grid was 90x90x1 to provide enough cells between producers and injectors.

Production was allocated among wells during the period of times where only field production rates or group production rates were available. Allocating production among wells introduces the potential for significant error in individual-well production rates, which would obviously affect significantly the accuracy of results based on these individual-well data.

I first attempted to build a multilayered simulation model (5 layers) thinking it necessary to model accurately the poor vertical sweep efficiency observed in Cut Bank field. Also I started modeling the entire 71 years of production history. This proved impossible mainly because of software and hardware limitations. As stated previously, we were using almost three times the maximum number of parameters recommended by SimOpt. This situation was reflected in slowing down the regression process to an impractically slow rate. Iterations would take much more than 8 hours when it ran at all.

Ultimately, I conducted a single layer analysis introducing pseudo relative permeability curves to reproduce the water bypassing effects due to gravity segregation and higher permeability near the base of the Cut Bank sand. Also I scaled back the simulation time to the last 20 years of history where I had production and injection data on a well basis. However, I ran a simulation from the beginning of production history until 1963 and output restart data (fluid saturations and pressure fields) to be used to initialize properly the simulation model.

I first used pseudo relative permeability curves to obtain a rough match of the unit-wide producing water-cut. Fig. 22 shows the initial relative permeability curves obtained from correlations and the pseudo relative permeability curves used to get a match of unit-wide water cut. Figs. 23-25 show comparisons of simulated to observed performance on a field-wide basis.

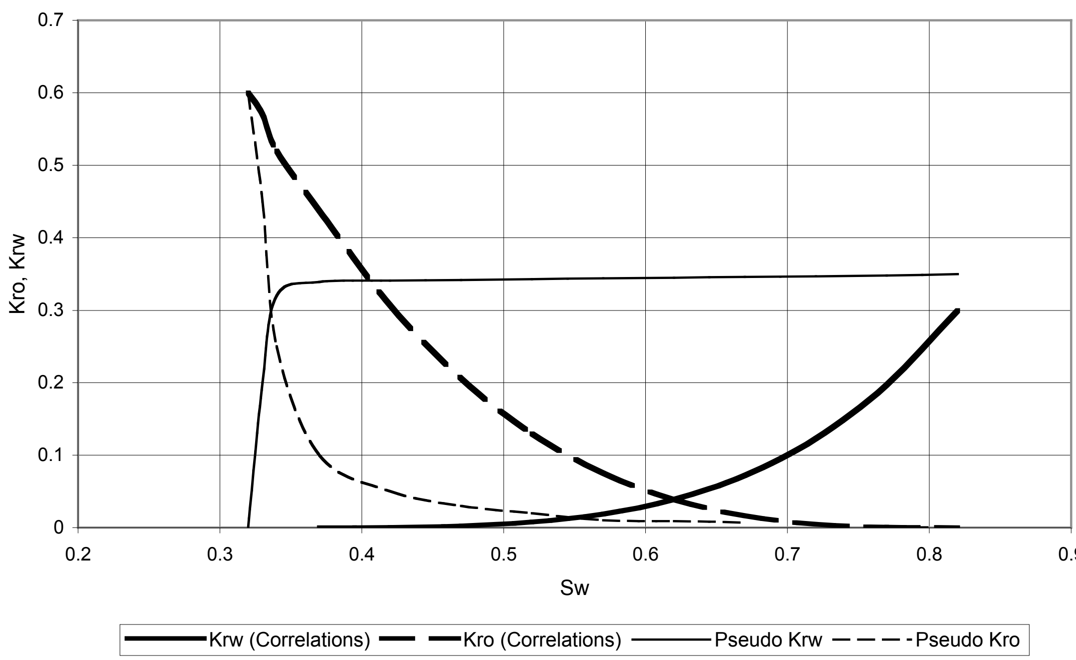

Fig. 22—Relative permeability curves from correlations were replaced by pseudos

I performed the regression on the actual production and injection history of 172 wells included in the actual data set. Instead of starting with a uniform permeability distribution, I started the regression with an initial permeability distribution derived from a correlation between core porosity and permeability data (Fig. 26). The regression attempt was unsuccessful. It resulted in very little improvement in the match, as can be seen in Figs. 23-25. Fig. 23 shows a field water cut comparison between the history data and the simulated data before and after regression. Fig. 24 shows the same comparison for field oil production rates and Fig. 25 for field water production rates. In addition, the regression yielded formation permeabilities that were unreasonably high in parts of the reservoir.

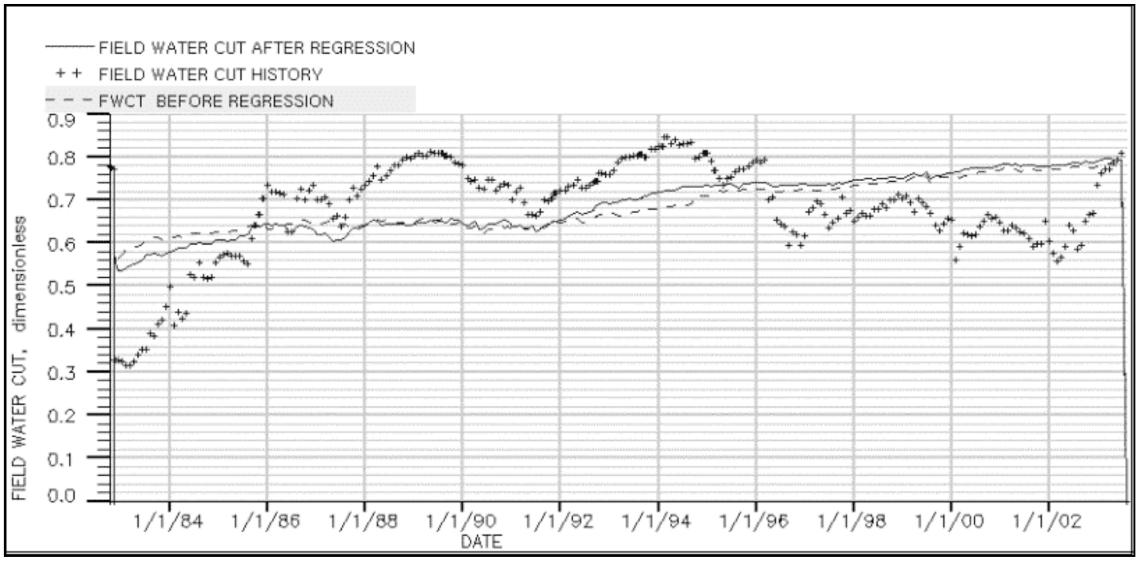

Fig. 23—Comparison of simulated to observed field water cut

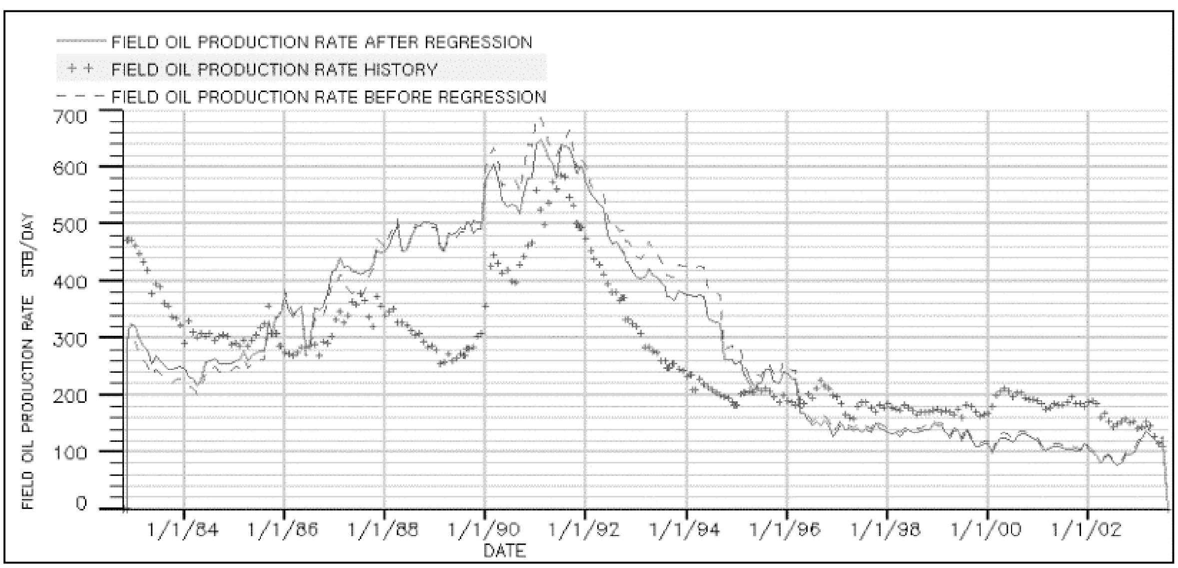

Fig. 24—Comparison of simulated to observed field oil production rate

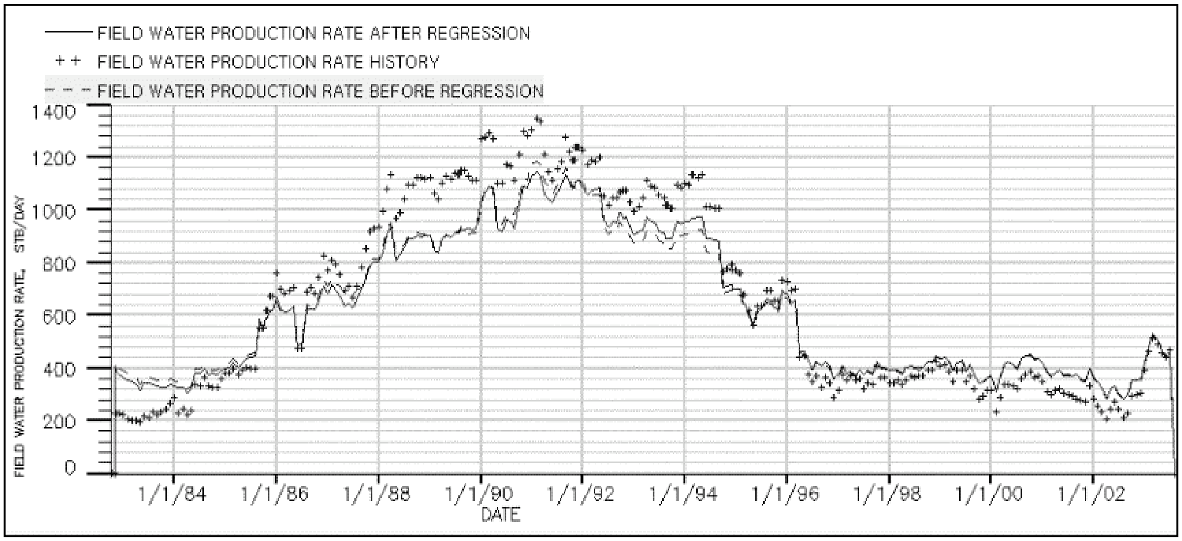

Fig. 25—Comparison of simulated to observed field water production rate

I attribute the inability to get a reasonable match to both software limitations and problems with the production and injection database. I think the greater cause, however, is problems with the production and injection database, in particular, the lack of individual well production data.

Thus, the model resulting from the field-wide match of water-cut (permeability map in Fig. 26 and match results in Figs. 23-25) represents our best model of the SCCBSU. I ran the automated infill incremental recovery determination procedure using this model, which resulted in the map of incremental oil recovery shown in Fig. 27.

Examination of Fig. 27 indicates two main regions with infill potential located in the northwest and southwest areas where red shade is observed. I caution that there is considerable uncertainty in these results and that further study is required to select specific infill locations.

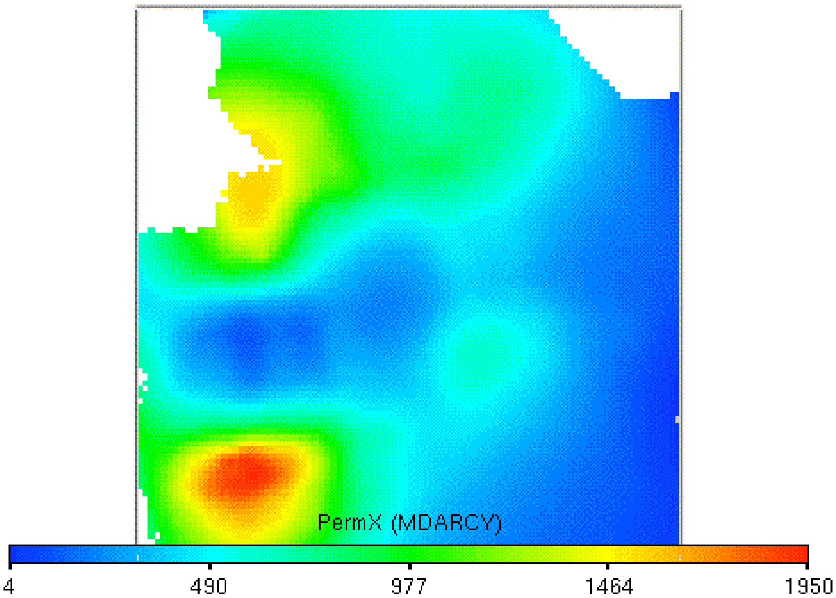

Fig. 26—Permeability map generated from correlation between porosity and permeability

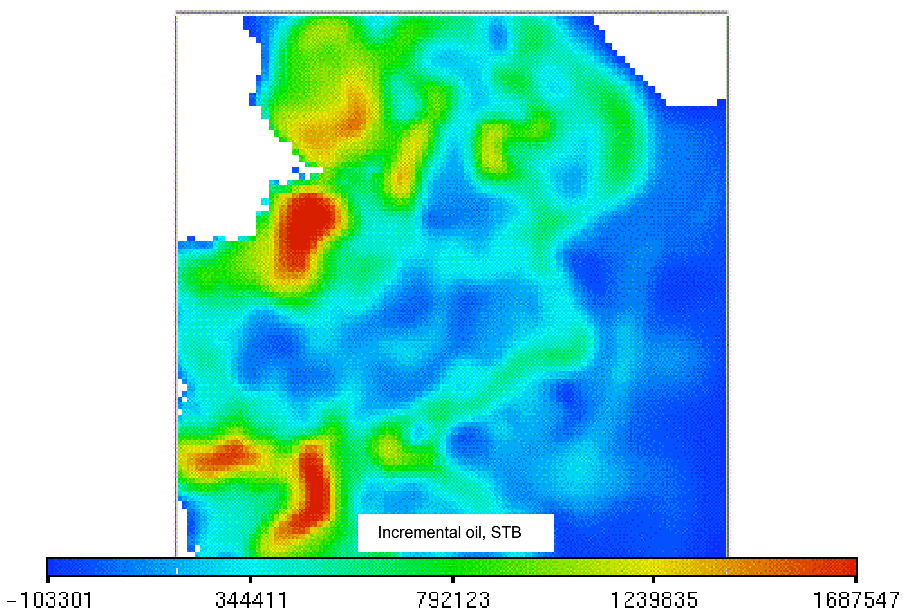

Fig. 27— Map of infill incremental oil recovery for the actual case

That I was able to match a synthetic model of the SCCBSU with 192 wells indicates the viability of the simulation-based methodology for rapid assessment of infill potential. However, since the method is based primarily on production and injection data, it is critical to have an accurate production and injection database. Time, effort and money must be spent in construction and quality control of the production database for the method to be of use.

CONCLUSIONS

The simulation-based regression approach presented in this thesis is superior to moving window statistical techniques in rapidly assessing infill potential due to its (a) similar time and cost requirements, (b) ability to more readily incorporate other data types, (c) multiphase capability and (d) greater accuracy.

In synthetic cases derived from Cut Bank field, the simulation-based regression approach successfully identified infill well locations with significant incremental potential.

Analysis of actual Cut Bank production and injection data using the simulation-based regression approach was unsuccessful, due to both problems with the Cut Bank production and injection database and limitations in existing commercially-available regression technology.

Since the method relies primarily on well locations and production and injection data, a complete and accurate production/injection database is required for the method to be of use.

RECOMMENDATIONS

Because of the problems experienced with the commercial regression technology I used, I recommend that fit-for-purpose regression technology be developed for implementation of this method. I recommend that the technology be proven on gas reservoirs before it is transferred to more complex oil reservoirs.

NOMENCLATURE

c_{di}	= calculated values
f	= objective function
f_{prior}	= objective function prior term
G_p	= best 12 consecutive months of production divided by 12
k	= permeability
k_{ro}	= oil relative permeability
k_{wr}	= water relative permeability
o_{di}	= observed values
r_{di}	= weighted difference between an observed value and a simulated one
R_s	= gas solubility
RMS	= Root Mean Square
SCCBSU	= South Central Cut Bank Sand Unit
σ_d	= measurement error for the d'th data set
v^k	= vector of current parameter normalized modifier values
w_d	= overall weighting for the d'th data set
w_{di}	= weighting for the i'th data point of the d'th data set

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